



# Detecting Cancer Metastases on Gigapixel Pathology Images

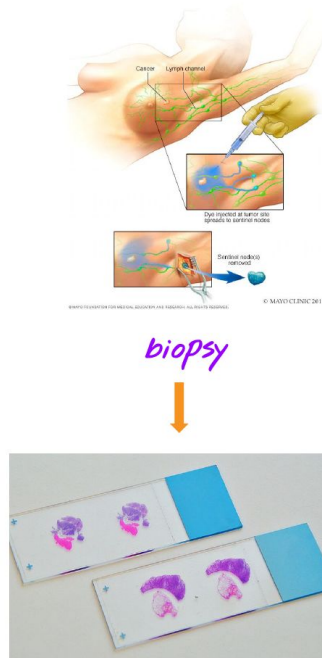
COMS 4995 Final Project

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# Background

## Visual inspection

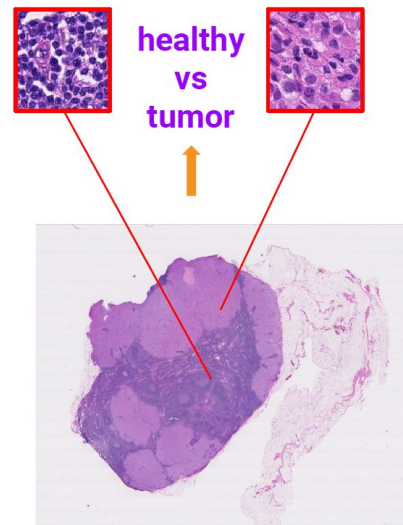
- Can be tedious and error prone (despite best efforts of pathologists).
- Tissue samples are volumes: when sliced, many images / sample.



Preparation



Diagnosis → Treatment plan

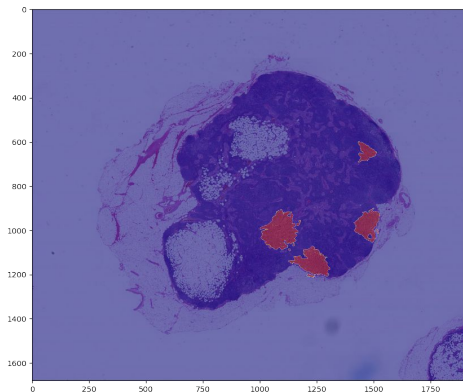


Visual inspection

# Goal

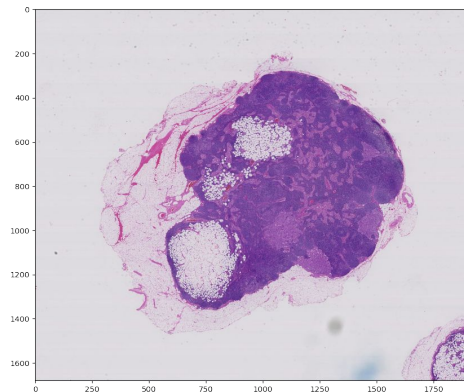
Given a collection of training data,  
develop a model that outputs a  
Heatmap showing regions of a  
biopsy image likely to contain cancer.

**Assist, not automate:**  
insert into workflow as an automatic  
second opinion, with enough training  
data, we can develop models radically  
reduce misdiagnosis at little cost.



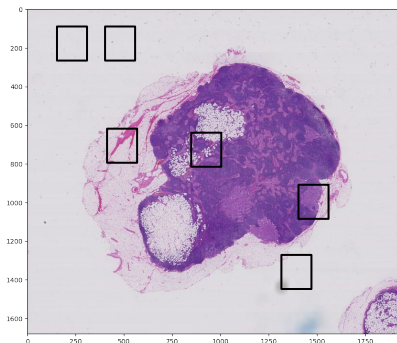
Ground Truth

(Red region: has tumor)

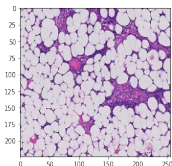


slide

# Methodology



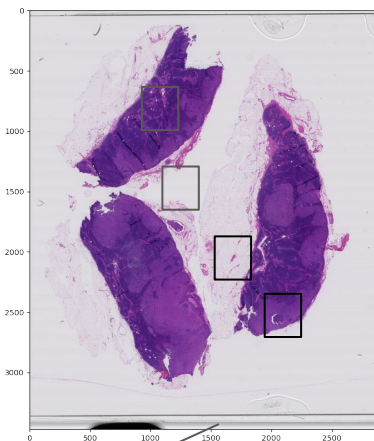
Patch extraction



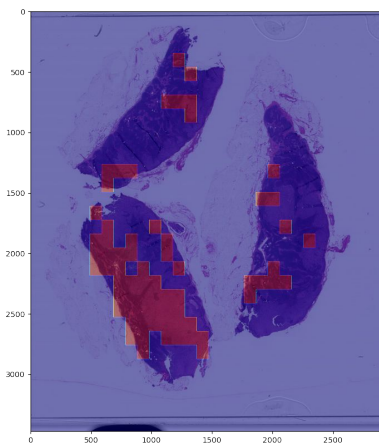
1). Single scale fully connected model or

2). Multi scale fully connected model

Train with deep learning model

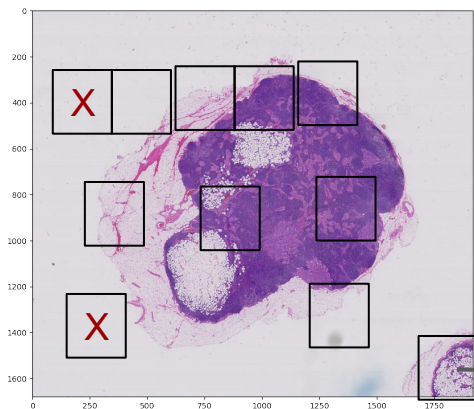


Use trained model to predict the probability of containing tumor cell in each sliding windows



Based on the probability, reconstruct the predicted 'heatmap'

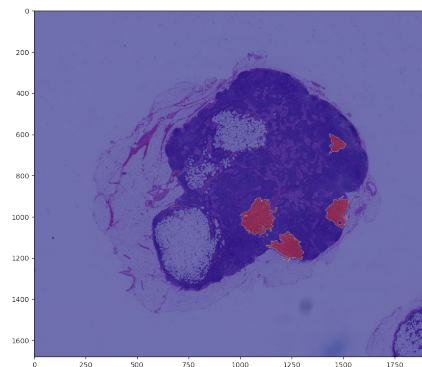
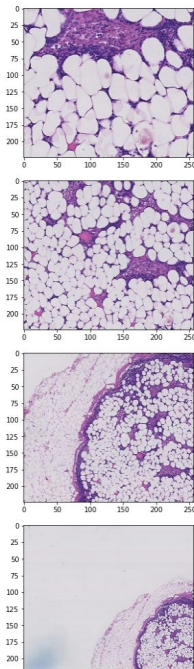
# Patch Extraction



Sliding window over the entire slide

Check if the patch has >50% tissue

For each patch, extract more patches at different zoom levels(level = 3,4,5,6)



Compare with corresponding tumor mask file to check if each patch includes tumor cell.

- For tumor pixel: collect that patch(includes one or more zoom level) with label 0
- For healthy pixel: collect that patch(includes one or more zoom level) with label 1



Repeat this process and generate labeled data set for all 10 slides. (for computational consideration, we used only 10 slides to speed up the algorithm)



# Model

Inspired from paper, we implemented two models as below:

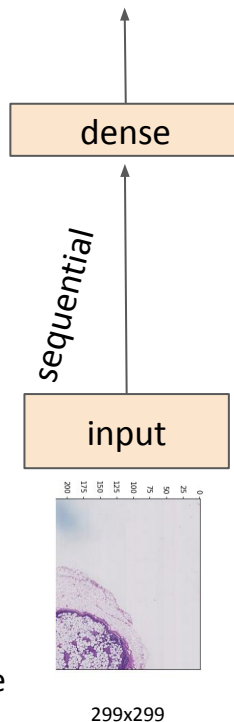
- Single Scale Model: InceptionV3 model previously trained on the imagenet with single level input
- Multi Scale Model: InceptionV3/VGG16 model previously trained on the imagenet with 4 different zoom levels inputs.

(Imbalanced data) Notice that over 90% patches contain healthy cells, when constructing train dataset, we

- 1) Randomly select healthy patches with probability of 0.5
- 2) Use data augmentation inspired from the paper(color perturbations and flip/rotate augmentation) to increase the proportion of tumor patches.

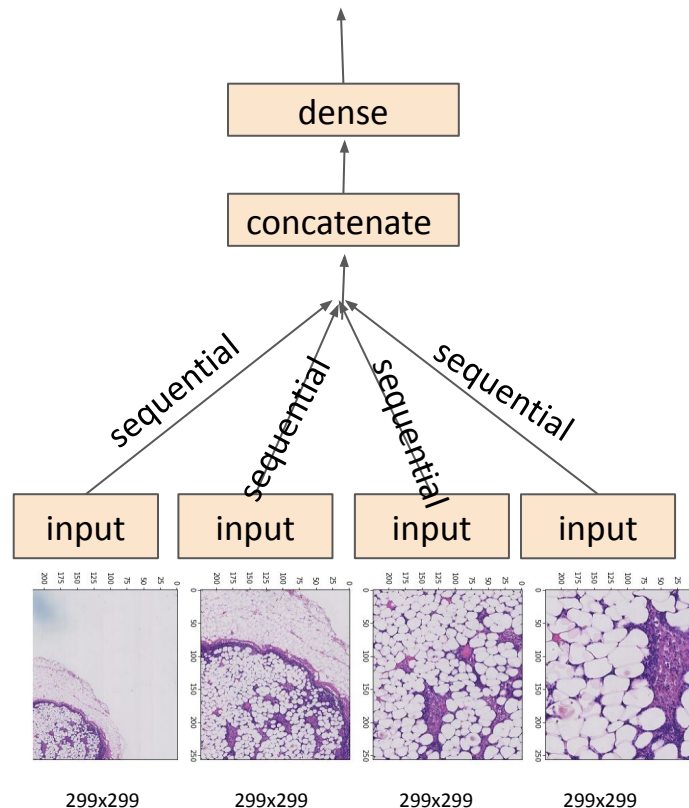
Single Scale

Has tumor? Yes or no



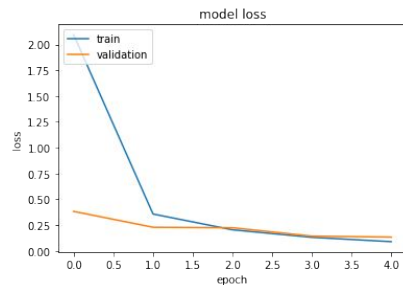
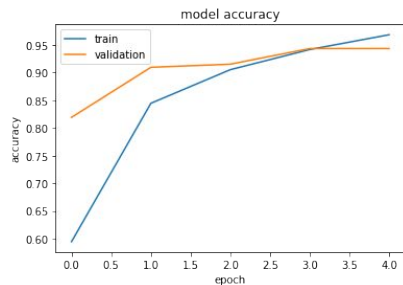
Multi Scale

Has tumor? Yes or no

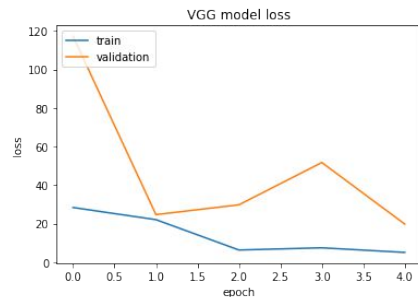
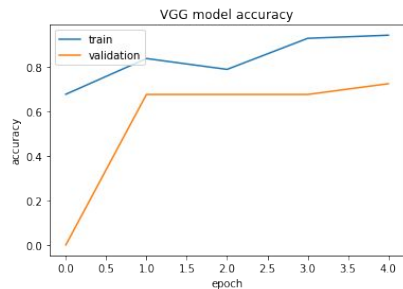


# Result

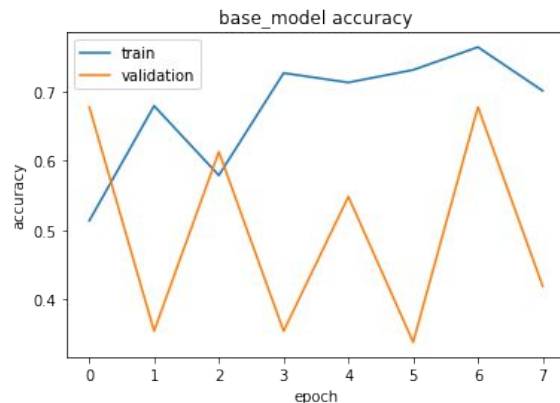
Multi-scale model(InceptionV3): (test set accuracy: 0.96)



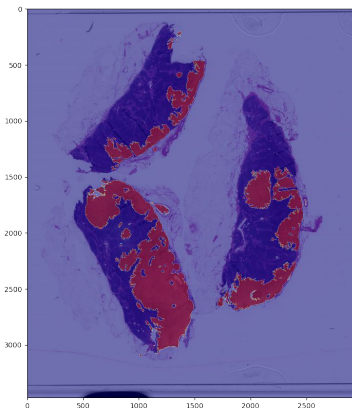
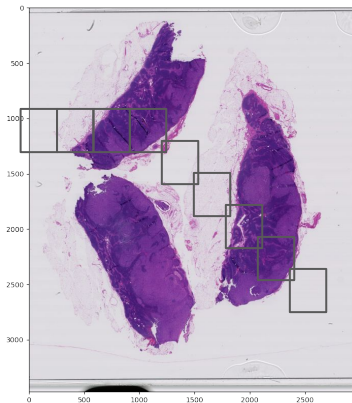
Multi-scale model(VGG): (test set accuracy 0.88)



Single-scale model(InceptionV3):

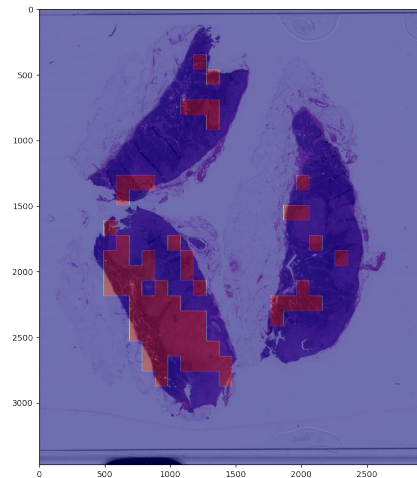


# Heatmap Reconstruction



After training the multi-scale model, we predict the tumor probability on each sliding window on the test slide. Then reconstruct the probability heatmap.

By adjusting the threshold (eg, from 0.5 to 1), we have smaller or larger red region (eg, predicted tumor probability  $> 0.5$  to predicted tumor probability = 1) depending on how specialists want to penalize the false negative case.



Left upper figure: slide078

Left lower figure: slide078 cancer cell ground truth

Right figure: red region shows where predicted tumor probability = 1



# Code Walkthrough

<https://colab.research.google.com/drive/1ES2tPDFm9Qol5fabeNrjYB4f7xQKQle5#scrollTo=BE6enDmmFq3M>

# Future Work

- Metrics: add more metrics: eg. precision-recall metrics
- Model: Fine tune the existing Inception V3 model and try ensemble method(includes more models and give majority vote)
- Note that the current test accuracy seems very high, we suspect this happens since majority of test dataset are healthy cells.

Source paper:

Detecting Cancer Metastases on Gigapixel Pathology Images

<https://arxiv.org/pdf/1703.02442.pdf>